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# Enhancing Environmental Education and Ecological Systems Sustainability in Higher Education through Predictive Artificial Intelligence Modelling

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## ABSTRACT

*Environmental degradation, intensifying climate instability and Artificial Intelligence (AI) utilization of technologies are restructuring the higher education (HE) sector in grooming scholars for sustainable futures. Higher Educational Institutions (HEIs) are saddled with the responsibility of providing environmentally and technologically competent HE capable of addressing the complex socio-ecological challenges as ecosystems approach irrevocable tipping points. Inspite of the rapid developments in AI-driven environment laboratories, sustainability curricula in HEIs are not sufficiently incorporated with predictive ecological intelligence and data-driven learning skills. It is on this premise that the current study investigates how predictive AI modelling, as well as deforestation estimations, biodiversity monitoring, carbon sink modelling and water stress simulations can enhance environmental education research and ecosystems sustainability in HEI spaces. Guided by the Complexity Theory, the Systematic Literature Review methodology with PRISMA protocols was adopted for the study. The findings brought to the fore the enhancement of interdisciplinary engagement and enhanced students' capacity in addressing complex environmental phenomenon and datasets for sustainability decision-making through the sterling applications of AI-supported learning environments. It is also germane to elucidate the persistent challenges such as inadequate digital infrastructure, limited lecturer competences, associated algorithmic transparency/ethics challenges, as well as unequal access to AI technologies across the Global South HEIs. In essence, this study advances HE by promoting AI literacy, ecological awareness, sustainability competences, and ensures futures-oriented environmental capacity building as entrenched in SDGs 4 and 13..*

**Keywords:** Artificial Intelligence (AI); Ecosystems Resilience; Environmental Geography; Environmental Sustainability; Higher Education; Predictive AI Modelling.

## 1. INTRODUCTION

Mankind is greatly saddled with confronting environmental sustainability challenges at the precipice of ecological, technological, and educational imperatives in the twenty-first century (Hughes, 2018; Rahimi & Oh, 2024). Manifestations of environmental degradation typified by biodiversity loss, increasing desertification, escalating hydrological stress, and the rapid atmospheric carbon build-up are collectively culminating in irreversible tipping points worldwide (Talukder et al. 2021; Jain al. 2024). Concurrently, the preponderance of Artificial Intelligence (AI) technologies is imperatively reshaping scientific inquiry, professional practice and knowledge production across all fields of human endeavour (Williamson, 2020; Dai, 2023). With reference to the quest for environmental conservation and technological development, Higher Education Institutions (HEIs) are germane players and principal architects of the intellectualism through which environmentalists, scientists, policymakers, and citizens interpret ecological complexity, as well as being the harbingers and cultivators of transformative sustainability competencies (Becher & Kogan, 2025; Hwami & Bedeker, 2025). From the foregoing, it is therefore imperative not just to modernise environmental and ecological curricula but to significantly rethink the pedagogical infrastructures that ecology and environmentalism are communicated, enacted and hinged upon.

Environmental education has considerably evolved (since the 1977 Tbilisi Intergovernmental Conference) as a formal academic niche, with established environmental awareness, knowledge, attitudes, skills, and participation as its core disciplinary mandate (Dorn, 2020; Payne, 2022). Global entities such as the UN Decade of Education for Sustainable Development, the Sustainable Development Goals (SDGs), particularly on Quality Education (SDG 4), Climate Action (SDG 13) and the 2022 Kunming-Montreal Global Biodiversity Framework, have increased the expectations on HEIs towards producing capable scholars that can address complex socio-ecological systems (Glavič, 2020; Kopnina, 2020). From the foregoing, empirical studies reveal that HEI sustainability curricula keeps relying majorly on purely descriptive and obsolete instructional resources that are inadequately equipped for communicating the dynamic nature of ecological challenges (Bakar, 2021; David, 2025). It is on this premise that predictive AI modelling acts as a transformative pedagogical front-runner. AI-driven environmental models, (such as machine learning-based deforestation projections, deep learning biodiversity monitoring, neural network water stress investigations, platforms, and carbon sequestration modelling) addresses the spatial heterogeneities, complex temporal dynamics and feedback mechanisms that characterise ecological systems (Gazya et al. 2022; Martínez-García, 2022). When properly integrated into HE curricula, these tools support instruction with technological support as well as enabling students to engage with real-world environmental datasets, provide predictive scenarios, and promote sustainability literacy (Huang, 2018; Katsamakas et al. 2024).

With respect to this study, predictive AI modelling applies machine learning, statistical AI algorithms and deep learning in analysing historical spatio-temporal data on the environment as well as forecasting ecological phenomena and trajectories (Alotaibi & Nassif, 2024), while environmental education are interdisciplinary pedagogical processes aimed at developing the knowledge, critical thinking, resourcefulness, and action competencies required for responsible environmental stewardship across formal and non-formal learning settings (Wani et al. 2024; Pimenow et al. 2025). Ecological systems sustainability denotes the long-term ecosystems resilience toward maintaining their functioning, structural integrity and adaptation capabilities in the face of anthropogenic and climatic interventions (Li et al., 2020). Sustainability literacy encompasses the constellation of competencies, (such as systems thinking, anticipatory thinking, normative reasoning, strategic action, and interpersonal collaboration) that enable individuals to contribute meaningfully to sustainable development (Roostaie et al. 2019; Nelson et al., 2020). The foundational principles underpinning this study are multifaceted. First is the principle of epistemic complexity which elucidates the emergent, nonlinear, and adaptive nature of ecological systems and which demands for educational approaches that model this complexity (Preiser et al. 2018). Second is the transformative pedagogy principle, which asserts that genuine environmental education must catalyse deep cognitive, affective, and behavioural transformation in for learning (Ajaps & Forh-Mbah, 2022; Farooq, 2023). Third is the technological equity principle, which advocates for AI integration in environmental education bearing in mind AI literacy levels, structural disparities in digital infrastructure, as well as institutional capacities of the Global South, in a bid to avoid technological advancement deepening educational inequalities of the region (Yigitcanlar et al. 2021). It is also imperative to exemplify that several fundamental concerns should be considered in the fusion of AI and environmental education, such as techno-optimism, (i.e. the position which assumes that AI tools enhance learning outcomes and ecological understanding (Bánkuty-Balogh, 2021; Birhane et al., 2021). Empirical studies debate this assumption on the premise that AI tools can reduce complex ecological phenomena to algorithmic outputs, thereby culminating into data dependency, which is opposed to critical ecological thinking (Bánkuty-Balogh, 2021; Sætra, 2023). A second debate relates to concerns algorithmic transparency and epistemic trust. Predictive AI models are limited in terms of interpretability, thereby raising questions about how students can engage with, evaluate, and critically contextualise AI-generated environmental predictions within educational settings (Almalawi et al. 2024; Susnjak, 2024). This challenge is compounded in environmental education settings when the ethics of misinterpreted ecological forecasts influencing conservation policies, climate adaptation strategies and land-use decisions are considered (Dillon & Herman, 2023). Thirdly, digital and infrastructural inequality poses as a major challenge in the Global South, as well as the Sub-Saharan African (SSA) HEIs, where epileptic electricity supply, poor internet connectivity, insufficient computational infrastructure, and inadequate institutional investment in AI collectively challenge AI integration in sustainability curricula (Oosthuizen & Motsatsi, 2025). If the right policies are not entrenched, the transformative potential of predictive AI modelling in environmental education becomes a mirage in the Global South and risks remaining the exclusive privilege of well-resourced HEIs in the Global North. The fourth principle relates to the substantive debate regarding the ecological footprint of AI itself. The computational infrastructure underpinning large-scale AI models consume significant ecological resources, which generate carbon emissions that confront environmental sustainability objectives driving their educational applications (Leon, 2024; Sharma & Kaur, 2025). This controversy demands that environmental education engaging with AI tools simultaneously cultivates critical awareness of the socio-environmental costs of AI infrastructure.

Problem Statement: Despite the convergence of escalating ecological crises and rapidly advancing AI capabilities, sustainability curricula within HEIs, particularly across the Global South remain critically under-integrated with predictive AI modelling tools and methodologies. Existing environmental education frameworks continue to rely on predominantly static, descriptive, and discipline-siloed instructional approaches that are structurally inadequate for developing the systems thinking, complexity awareness, and the required futures literacy required to navigate twenty-first-century socio-ecological challenges (Green et al. 2021; Peretz, 2025). While literature confirms the transformative potential of AI-driven ecological models for scientific research and policy analysis (Secundo et al., 2025; Santos & Carvalho, 2025), their systematic integration as pedagogical instruments within HE remains nascent, theoretically underdeveloped, and empirically underexplored (Aparicio et al., 2021; Bakar, 2021). Furthermore, challenges militating against institutional digital infrastructure, preparedness of academic instructors, responsible AI-policy adoption frameworks, as well as the best-suited AI applications to the environmental realities and educational challenges experienced in SSA and the Global South in general. It is on this premise that this study addresses the research gap on AI-enhanced pedagogy, environmental education scholarship, and ecological sustainability, offering evidence-based insights required by HEIs navigating this complex terrain. In essence, the study anchors the research question: “To what extent does the integration of predictive AI modelling into HE curricula enhance environmental education outcomes and contribute to ecological systems sustainability, and what pedagogical, institutional, and policy conditions are necessary to optimise this integration across diverse HEI contexts?

## 2. METHODOLOGY

The Systematic Literature Review (SLR) methodology was conducted for the study (Torres-Carrión et al., 2018; Lame, 2019; Higgins et al., 2022).Also, the Population, Intervention, Comparison, Outcome, and Context (PICOC) framework guided the SLR formulation based on the research question (Eriksen & Frandsen, 2018; Amir-Behghadami & Janati, 2020): Population refers to the students, educators, and HEIs; Intervention connotes the process of integrating predictive AI modelling tools such as deforestation projections, water stress simulation investigations, platforms for biodiversity monitoring, as well as the applications on carbon sink modelling, while Comparison relates to conventional approaches for non-AI-integrated environmental education. Outcome is defined as the enhanced environmental education outcomes, for example, ecological literacy, complexity awareness, systems thinking, sustainability agency, etc, while Context refers to the HEIs across diverse geographic, institutional, and socio-economic settings most especially in the Global South.

Eligibility Criteria

Inclusion Criteria: Included studies that were considered eligible in the SLR was based on the following criteria:

Thematic Relevance: Studies that addressed the application, integration, or predictive AI modelling pedagogy dimensions like machine learning, neural networks, deep learning, and environmental education tools for AI-driven simulation, sustainability curricula or ecology in HEIs.

Educational Focus: These included studies on AI-environmental integration from educational dimensions, as well as pedagogical approaches, educator preparedness, curriculum design, learner outcomes, institutional policies and frameworks on capacity-building. Technical AI articles without educational dimensions were excluded.

HE as Study Focus: Studies focused on HE, e.g. universities, universities of technology, polytechnics, and vocational HEIs were included. Primary/secondary education studies were excluded unless there were substantial methodological/ theoretical explanations that were applicable to HEIs.

Publication Type: These include Peer-reviewed journal articles, chapters in scholarly edited volumes, conference proceedings and policy documents produced by renowned international organisations (World Bank, UNESCO, UNEP, IPCC, AU among others) were included accordingly.

Temporal Scope: These include studies published post-2018 that reflect findings on AI capabilities and machine learning in the geography and environmental science palace, and their integration in education.

Language: These include articles published in English language, as well as studies published in other languages with full-text translations, e.g. published studies in Portuguese, French, and Spanish with relevance to Global South were included.

Exclusion Criteria Excluded articles include technical articles on algorithms, or AI computational models that was void of educational or pedagogical analysis; AI integration studies in non-environmental disciplines that had no interdisciplinary relevance to ecological sustainability education; Grey literature of insufficient scholarly rigour, including blog posts, journalistic reports, and institutional marketing materials; Duplicate publications reporting the same study across multiple outlets, where only the most comprehensive version was retained; Studies for which full-text access could not be obtained despite exhaustive retrieval efforts through institutional library access, interlibrary loan, and author correspondence.

Search Strategy and Database Selection

Six database searches were consulted based on comprehensive indexing, their disciplinary breadth and those relevant to the multidisciplinary stance of the study on environmental science, educational research, AI, computer science as well as sustainability studies:

Scopus: selected based on its wide coverage of peer-reviewed studies in the applied natural sciences, social sciences, and engineering disciplines, and for its citation analytics and Boolean search functionality.

Web of Science (WoS): selected for quality indexing, multidisciplinary, and wide network of citations on AI applications in education and ecology.

ScienceDirect (Elsevier): selected for its wide array of environmental science studies, ecological modelling articles as well as studies on sustainability and educational technology with relevance to the thematic focus of the study.

ERIC: Also known as the Education Resources Information Centre was selected as a specialised database for education studies, pedagogy, curricula and scholarship in HE.

Google Scholar: This supplementary database captures multidisciplinary, and open-access publications that were not indexed in other subscription-based databases, but particularly captured publications from Global South HEIs.

African Journals Online (AJOL): These category of publications were included to add African HEI dimensions on environmental education, AI integration, and sustainability pedagogy.

Search String Development and Piloting

Search strings were developed from seminal publications to optimise both comprehensive/specific results and excluding irrelevant results. Boolean operators (such as AND, OR, NOT), truncation symbols (*), and phrase markers (" ") were adopted across the 6 databases and adapted to the syntax requirements for each of the 6 platforms. The primary search string, adapted for each database interface, was structured as follows:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive modelling" OR "AI model*" OR "neural network*" OR "predictive simulation*") AND ("environmental education" OR "sustainability education" OR "ecological literacy" OR "climate change education" OR "education for sustainable development" OR "ESD" OR "green curriculum") AND

("higher education" OR "university" OR "tertiary education" OR "higher education institution*" OR "HEI*" OR "undergraduate" OR "postgraduate") AND ("deforestation" OR "water stress" OR "biodiversity" OR "carbon sink*" OR "ecosystem*" OR "ecological system*" OR "environmental monitoring" OR "remote sensing" OR "GIS" OR "geospatial").

Screening and Eligibility Assessment

Identification and Deduplication

The systematic database searches yielded a total of 4,847 records across all six databases and supplementary sources. All retrieved records were exported into Rayyan, a specialised systematic review management platform that facilitates collaborative screening, blinding, and conflict resolution (Kellermeyer et al. 2018). Automated deduplication within Rayyan, supplemented by manual verification, identified and removed 1,203 duplicate records, leaving 3,644 unique records for title and abstract screening..

## 2.1. Theoretical model

The Complexity Theory is the framework underpinning the study and it provides a theoretically coherent, practically generative and epistemologically robust framework that guides the analytical direction and policy direction of the study. Figure 1 diagrammatically depicts the complex theory.

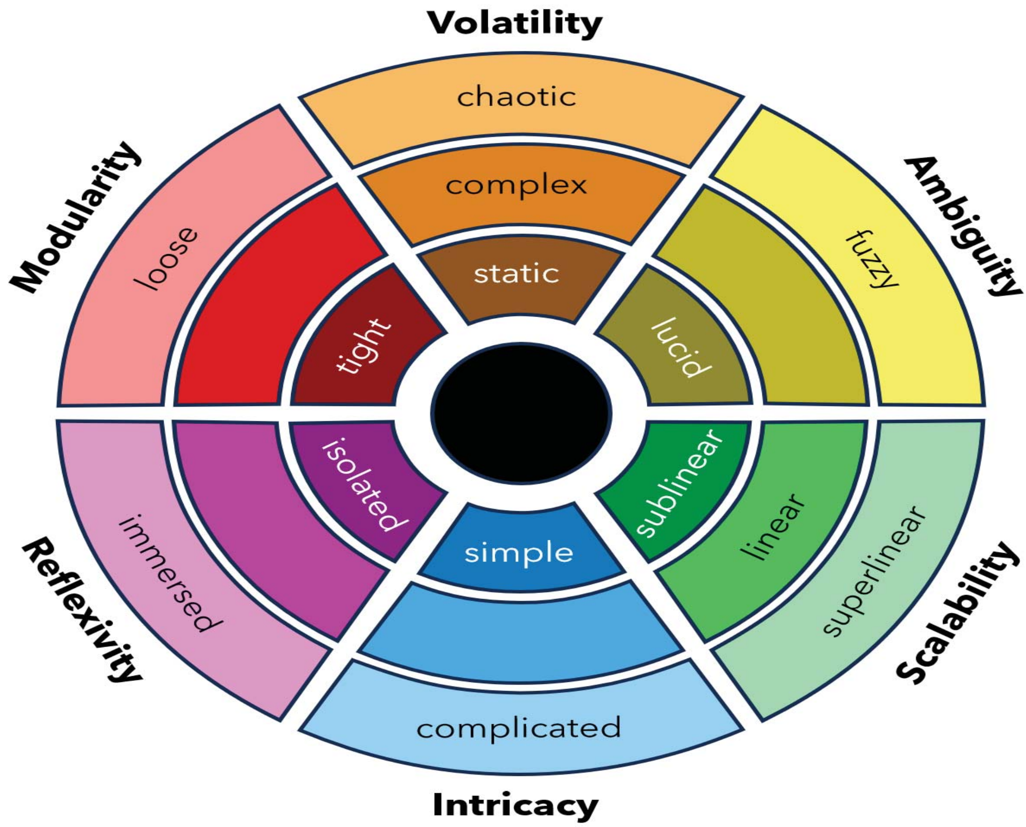


*Figure 1: A conceptual diagram of the Complexity Theory (Unfix, 2024).*

## 3. FINDINGS

### 3.1. Effects of the various factors on the coefficient $R_p^2$

The findings for the study were analysed based on the  Complexity Theory and all findings were analysed through pedagogical perspectives that were most appropriate to the intellectual underpinning of the study.

Global Patterns of AI Modelling in Higher Environmental Education

Findings reveal that with the preponderance of predictive AI modelling in global higher environmental education, its integration across geographic, disciplinary, and socio-economic settings still remains nascent, uneven and institutionally fragile. In terms of geography, findings revealed that the Global North HEIs are more versatile in the utilization of AI-enhanced environmental education and practice, while a reverse scenario depicts the Sub-Saharan African (SSA) HEIs,  with Nigeria, South Africa and Kenya accounting for the vast majority in the region. This geographic skew in the evidence base is reflects disparities in AI infrastructure investment, digital connectivity, institutional research capacity, and policy prioritisation that constitute one of the study's most critical and actionable findings. Interpreted through the Complexity Theory, this geographic unevenness reveals a troubling pattern of asymmetric adaptive capacity within the global HE system. Complex adaptive systems derive their resilience and innovative capacity from the diversity of their constituent agents and the richness of their interactions (Carmichael & Hadžikadić, 2019; Scharte, 2025). A global environmental education ecosystem in which AI-enhanced pedagogical innovation is concentrated in a small number of well-resourced, predominantly Global North institutional contexts represents a system of dangerously reduced diversity, one in which the epistemic resources, contextual knowledge, and place-based ecological understandings of Global South HEIs are systematically excluded from the collective intelligence that environmental education urgently requires. This finding resonates powerfully with Khoza & Van Der Walt's (2025) diagnosis of on AI-enhanced pedagogies in HE in South African AI-enhanced pedagogy.

**Typology of Predictive AI Models in Higher Environmental Education**

Findings depict four primary categories of predictive AI modelling tools integrated within higher environmental education curricula, each with distinct pedagogical affordances, data requirements, and ecological learning domains:

Deforestation Forecasting Models, employing machine learning algorithms trained on multitemporal satellite imagery, land-use change datasets, and socio-economic drivers, constituted the most frequently reported AI modelling type. Platforms including Google Earth Engine with integrated random forest classifiers, the Global Forest Watch AI monitoring system, and institutional custom-built convolutional neural network models were most commonly referenced. These tools were most frequently integrated within environmental geography, tropical ecology, and conservation biology programmes, predominantly at postgraduate level, and in Latin American, Southeast Asian, and Sub-Saharan African institutional contexts where deforestation constitutes an immediate and locally salient ecological challenge.

Water Stress Simulation Models, utilising hydrological AI platforms, LSTM (Long Short-Term Memory) neural networks for streamflow prediction, and integrated climate-hydrology models. The NASA SERVIR platform, the World Resources Institute's Aqueduct Water Risk Atlas with AI-enhanced projections, and university-developed ArcGIS-integrated water stress modelling tools were most commonly employed. These tools appeared most frequently in arid and semi-arid region HEI settings, including South African, Australian, Middle Eastern, and southwestern United States institutions where water scarcity constitutes both a locally relevant pedagogical context and an urgent institutional sustainability challenge.

Biodiversity Monitoring Platforms, integrating AI species identification, acoustic monitoring neural networks, habitat suitability modelling, and extinction risk prediction algorithms. Platforms including iNaturalist with automated species identification, the IUCN Red List integrated with machine learning extinction trajectory modelling, and BirdNET acoustic AI monitoring tools were most commonly referenced. These tools were most frequently integrated within conservation biology, wildlife management, and environmental science programmes, with particularly strong representation from Australian, South African, and Brazilian HEI contexts characterised by exceptional biodiversity and conservation urgency.

Carbon Sink Modelling Applications, employing AI-driven vegetation carbon stock estimation, forest biomass neural networks, and integrated carbon cycle simulation platforms, were elucidated by scholars such as Jahan, (2024) and Xu et al. (2025). The Global Carbon Project's AI-enhanced carbon budget models, NASA's Carbon Monitoring System, and FLUXNET AI-integrated eddy covariance data analysis platforms were most commonly reported. These tools were predominantly integrated within climate science, environmental engineering, and sustainability management programmes at research-intensive universities, reflecting the technical data literacy requirements of carbon cycle modelling. Notably, studies such as Sharma et al. (2023) and Rahmati, (2024) reported the integration of multi-domain AI modelling environments that combined two or more of the above categories within integrated ecological systems simulation platforms.

### Comparative Analysis with Prior Scholarship

These findings significantly extend and contextualise prior reviews of AI in education (Michel-Villarreal et al. (2023; Castillo-Martínez et al. 2024) and technology integration in environmental education (Fernández et al. 2019; Husamah et al., 2025). Where Michel-Villarreal et al's (2023) landmark review of AI in HE identified personalised learning, assessment automation, and intelligent tutoring as the dominant AI application domains, the present review reveals that ecological modelling and environmental simulation constitute a distinct and rapidly growing fourth domain of AI educational application, i.e. one with unique pedagogical affordances rooted in the complexity and urgency of environmental crisis. Similarly, where Liu et al.'s (2019) study on virtual environments in environmental education predates the machine learning revolution and therefore documents primarily game-based and virtual reality simulations, this study captures a distinct generation of AI tools whose predictive power, real-world data grounding, and spatiotemporal granularity represent a fundamental advancement in the capacity of educational technology to engage learners with ecological reality. In essence, this finding aligns with the Complexity Theory. From the foregoing, integrated multi-domain models depict feedback dynamics, and emergent features of ecosystems than single-domain tools, thus equipping students with a more challenging representation of ecological complexity (Boca & Saraçlı, 2019; Jin & Zhong, 2026).

### Pedagogical Mechanisms Through Which Predictive AI Modelling Cultivates Environmental Education Outcomes

This finding reveals that students that utilized predictive AI modelling within their HE curricula demonstrated ecological literacies and competences more than those that received conventional instructions. This finding is very evident finding on account of its educational justification for AI integration in higher environmental education. However, it is imperative to note that the quality and depth of ecological literacies varied substantially based on the pedagogy through which AI tools were utilized. Studies that integrated predictive AI models within constructivist, inquiry-based, and problemsolving pedagogical frameworks, wherein learners actively interrogated model assumptions, manipulated input variables, interpreted output scenarios, and debated the implications of predictions, consistently produced deeper, more transferable, and more durable ecological literacy outcomes than studies reporting passive exposure to AI-generated visualisations or pre-interpreted model outputs. This finding suggests that the educational value of predictive AI modelling derives from the quality of the pedagogical scaffold within which students engage with them.

Interpreted through Complexity Theory, this finding elucidates that the ecological understanding that constitutes genuine environmental literacy is an emergent property of the active, iterative, and socially embedded process through which students engage with complex ecological data, interrogate their own assumptions, and construct mental ecological models. Pedagogical designs that position learners as active complexity navigators are epistemologically essential for environmental education. This finding both confirms and significantly extends Talley & Hull’s, (2023) study on sustainability competencies, which identifies systems thinking as the foundational competency undergirding all other sustainability capabilities. Where Wiek et al. articulate systems thinking as a curriculum objective, the present review provides empirical evidence of the specific pedagogical mechanisms through which predictive AI modelling operationalises and develops this competency, thus advancing the field from normative aspiration to evidence-based practice.

Systems Thinking, Complexity Awareness, and Futures Literacy Development

The third most consistently reported pedagogical outcome of predictive AI modelling integration was the development of systems thinking, complexity awareness, and futures literacy, i.e.  the constellation of higher-order cognitive competencies most directly aligned with the theoretical predictions of Complexity Theory. Studies such as Mambrey et al. (2022) and Shutaleva, (2023) elucidated that cognitive outcomes beyond basic ecological knowledge acquisition, documenting evidence of enhanced systems thinking and improved capacity in identifying feedback loops, recognising emergent properties, reasoning about nonlinear causation, and understanding ecological threshold dynamics among students engaged with predictive AI modelling. This finding is theoretically significant because it provides empirical validation for Complexity Theory's pedagogical claim that tools capable of modelling complex system dynamics can cultivate complexity consciousness in students (Koopmans, 2020; Cabrera & Cabrera, 2023). Other studies particularly narrated the ability to think creatively and critically about the future, navigating uncertainties, and working toward sustainable alternative futures. These studies revealed that the scenario-based nature of predictive AI modelling (i.e. wherein students engage with multiple probabilistic future ecological states rather than a single deterministic projection) was particularly effective in developing futures literacy, cultivating anticipatory consciousness (i.e. the capacity to think across temporal scales, hold multiple future possibilities simultaneously, and act purposefully in the present with awareness of long-term systemic consequences).

**Interdisciplinary Integration and Collaborative Learning**

Another significant pedagogical finding concerned the capacity of predictive AI modelling to catalyse interdisciplinary engagement and collaborative learning within higher environmental education. Studies such as Dudysheva & Veryaev, (2024) and Peretz, (2025) reported that the integration of AI ecological modelling tools within environmental curricula prompted meaningful interdisciplinary engagement that draws students and educators across disciplinary boundaries to engage with the complex socio-ecological dimensions of AI-generated environmental forecasts. The most commonly reported interdisciplinary bridges were those between environmental science and social science (particularly environmental sociology, human geography, and political ecology), between ecology and data science or computer science, and between environmental studies and policy, law, and economics. This finding is theoretically consistent with Complexity Theory's emphasis on the generative educational value of diversity and interconnection within learning systems (Baskara, 2024). Predictive AI models, by rendering visible the systemic interconnections among ecological, climatic, hydrological, and socio-economic variables, naturally invite learners from diverse disciplinary backgrounds to contribute their distinct analytical frameworks to the collective interpretation of model outputs, producing the kind of emergent collective intelligence that Etukuru, (2024) identifies as the symbol of complexity-conscious educational design. The finding thus suggests that predictive AI modelling functions as a shared intellectual space within which diverse disciplinary perspectives converge and interact to produce understanding that transcends the boundaries of any single discipline.

**Barriers and Enablers of AI Integration in Higher Environmental Education**

The finding further unravelled that barriers based on the structure, pedagogy, ethics as well as institutional, hampered effective AI integration in the higher environmental education spaces, with more evidence in Global South HEIs (Asamoah & Amarteifio, 2025; Khan et al. 2025). The most common barriers include inadequate digital infrastructure, epileptic electricity supply, slow internet connectivity, limited infrastructure to successfully run machine learning applications, and restricted institutional access to AI software and ecology platforms/databases. This barrier was reported in African, South Asian, and Latin American HEIs, confirming the geographic dimension of digital inequality. The associated implications of this barrier in several SSA HEIs is such that predictive AI modelling exercises designed for implementation with ecological databases had to be redesigned or abandoned due to bandwidth limitations, epileptic power supply culminating in reducing practical modelling sessions, and insufficient RAM hampering the execution of machine learning algorithms on institutional hardware. These findings resonate with Maimela & Mbonde’s (2025) study on the documentation of AI in South African universities, when viewed from curriculum transformation and decolonisation perspectives, revealing a systemic pattern of technological exclusion that, if unaddressed, risks creating a new dimension of the educational imbalance if viewed as an educational aid or as an obstacle. Interpreted through Complexity Theory, infrastructural inequality represents a critical constraint on the adaptive capacity of Global South HEIs as complex educational systems. Complex adaptive systems require cognitive, technological, and institutional resources to respond adaptively to environmental perturbations and to evolve toward more sophisticated organisational configurations (Roundy et al. 2018). HEIs lamented the inadequate digital infrastructure which constrained their adaptive capacity, their technological opportunities and educational imperatives which predictive AI modelling represents. This is both an educational equity problem and a systemic sustainability problem, since the ecological knowledge and sustainability agency most urgently needed for planetary stewardship are also most urgently needed in the Global South communities most acutely vulnerable to ecological collapse.

**Human Capacity Barriers: Lecturer Preparedness and Pedagogical Confidence**

The second most frequently reported barrier was inadequate lecturer preparedness for AI-enhanced environmental education, which encompasses limited familiarity with AI modelling tools and platforms, insufficient data literacy for interpreting and contextualising AI-generated ecological outputs, uncertainty about appropriate pedagogical scaffolding for AI-mediated learning, and anxiety regarding the perceived threat of AI to academic expertise and disciplinary identity. This barrier appeared in 71 studies across both Global North and Global South HEI settings, though with greater intensity and breadth in the latter. Several studies reported that environmental science and geography academics whose professional identity is grounded in field-based observation, ecological expertise, and place-based knowledge experienced predictive AI modelling as epistemologically threatening, a technological encroachment on disciplinary knowledge domains they had spent careers developing.

**Ethical and Epistemological Barriers: Algorithmic Transparency and Epistemic Justice**

This barrier includes the challenges relating to the transparency of algorithms, model interpretations, data bias, and epistemic justice. Complex machine learning models, particularly deep learning neural networks whose decision-making processes cannot be easily interrogated based on their limited interpretability is a major pedagogical challenge, with its implications on how students can critically engage, and ethically evaluate AI-generated ecological data. This barrier from a Complexity Theory perspective insists on the recognition that complex systems are resistant to complete prediction (Thurner et al. 2018). Also, it is imperative to elucidate that predictive AI models do not resolve this challenge despite their computational capabilities, instead, they repackage it in probabilistic forecasts whose model assumptions and limitations associated with training data are invisible to unprofessional users. From the foregoing, some studies raised the epistemic justice dimension of this barrier especially in the Global South. Findings revealed that dominant AI environmental models are predominantly trained on datasets from Global North ecological contexts, employ algorithmic frameworks developed within Western scientific epistemologies, and generate ecological forecasts calibrated to the data environments and land-use patterns of temperate rather than tropical or semi-arid ecosystems. When applied to African, South Asian, or Latin American ecological contexts, these models may systematically misrepresent local ecological dynamics, underestimate context-specific vulnerabilities, or render invisible the Traditional Ecological Knowledge systems that provide irreplaceable insights into local ecosystem functioning. This finding constitutes one of the most theoretically significant contributions of this study, revealing that algorithmic bias in AI environmental models as a profound epistemic justice issue with direct implications for whose ecological knowledge counts, whose environmental vulnerabilities are made visible, and whose sustainability futures are prioritised.

**Institutional and Policy Barriers: Fragmentation and Governance Gaps**

Institutional and policy barriers such as fragmented inter-departmental coordination, disciplinary siloing that obstructs interdisciplinary AI-environment curriculum development, absence of institutional AI-for-sustainability strategies, and inadequate policy frameworks for responsible AI adoption were also stated in the literature. These findings reveal that even where individual lecturers possess the motivation and digital competence to integrate predictive AI modelling in their teaching, institutional structures frequently obstruct implementation through institutional bureaucracies, competitive departmental resource allocation, and absence of the cross-institutional policy frameworks and incentive structures that systematic AI curriculum integration requires. From a Complexity Theory perspective, these institutional barriers reflect the path dependence characteristic of complex adaptive systems: universities, like all established complex systems, tend to resist perturbation and return to established configurations, privileging the reproduction of existing pedagogical structures over the adaptive innovation that AI integration demands (Köpeczi-Bócz, 2025). Overcoming the institutional bureaucracies requires sustained policy pressure, resource reallocation, leadership commitment, and cross-institutional collaboration which the complexity theory suggests is necessary to shift complex systems toward new, more adaptive equilibrium states.

**Institutional Enablers of Supporting Successful AI Integration**

The findings also identified a constellation of institutional conditions consistently associated with successful, sustained, and educationally impactful AI integration in higher environmental education such as Institutional leadership commitment, which manifests through HEI leadership endorsing AI-for-sustainability pedagogical innovation, dedicated budget allocation for AI infrastructure and professional development, and formal policy frameworks embedding AI environmental education within institutional sustainability strategies. Structured networks of academics engaged in collaborative exploration and mutual support around AI-enhanced pedagogy are critical mediators of individual lecturer transformation, providing the reflective scaffolding that Wang & Zhang, (2026) identify as imperative for productive engagement with disorienting professional challenges. In addition, Open-access AI platforms and ecological data repositories such as Google Earth Engine, NASA Earthdata, the Global Biodiversity Information Facility (GBIF), and Open Street Map integrated with machine learning tools were opined as critical enablers of AI integration in resource-constrained HEIs, circumventing the financial barriers of proprietary AI software licensing and enabling institutions with limited computational resources to engage with real-world ecological datasets (Srivastava & Sharma, 2024; Retscher, 2025). Also, industry, government, and NGO partnerships that provide access to operational AI environmental monitoring systems, real-world ecological datasets, and professional mentorship for both academics and students were reported as powerful accelerators of AI-enhanced environmental education, bridging the gap between academic AI modelling and real-world ecological governance practice.

## 4. DISCUSSION AND CONCLUSION

### The Geography of Inequality: Global South Exclusion and Epistemic Justice Imperative

The finding that Sub-Saharan African HEIs contributed fewer integration-reporting studies despite encompassing some of the world's most ecologically significant and climate-vulnerable landscapes, constitutes what is arguably the most ethically troubling and politically consequential finding of the entire study. This is a manifestation of deeply structural global inequalities that directly undermine both the quality of environmental education available to African HEI students and the long-term capacity of African nations to develop the AI-literate environmental workforce required for ecologically informed sustainability governance. This finding resonates wholistically with Hwami & Bedeker, (2025) and Pietersen et al.’s (2025) critique of knowledge imperialism in African education which privileges Global North epistemologies, methodologies, and technological frameworks in African HEI curricula at the expense of locally grounded, contextually appropriate, and epistemically diverse educational approaches. In the AI-environmental education domain, knowledge imperialism manifests through the dominance of AI platforms developed, trained, and calibrated in Global North ecological and institutional contexts; the concentration of cutting-edge AI-environmental pedagogy research in Global North institutions whose findings are published in subscription-access journals inaccessible to many African academics; and the tendency of international capacity-building programmes to transfer AI tools and pedagogical models from North to South without adequate attention to contextual adaptation, institutional sustainability, or epistemic justice.

### Digital Infrastructure Inequality

This study also discovered from the findings that inadequate digital infrastructure constitutes as a major barrier to AI-enhanced environmental education in Global South HEIs with implications for sustainable development. While the digital divide has been extensively documented in the general HE literature, the present study demonstrates its specific manifestations and consequences within the domain of AI-enhanced environmental education, a domain where the stakes of exclusion extend beyond individual educational disadvantage to collective incapacity for the ecological governance that planetary sustainability demands. Hence,, this study suggests that Global South HEI environmental education is characterised by inequalities at all three levels: insufficient computational infrastructure constrains access; inadequate lecturer preparedness and AI literacy constrain effective use; and the absence of contextually appropriate AI tools and open-access ecological datasets constrains meaningful educational outcomes. Addressing digital inequality in AI-enhanced environmental education therefore requires capacity building, tool contextualisation, and open-access knowledge infrastructure development. This finding positions this study with the optimism of AI's democratising potential in education, that open-source AI tools and freely available ecological datasets can level the playing field between Global North and Global South HEIs by eliminating the cost barriers of proprietary technology. While the review confirms that open-access platforms have indeed enabled AI-environmental education in resource-constrained contexts, it simultaneously documents the persistent structural barriers such as bandwidth limitations, power supply unreliability, computational hardware insufficiency, and AI literacy deficits that constrain the effective utilisation of even freely available tools. The democratisation narrative thus revealed as significantly overstated in the absence of comprehensive infrastructural and capacity-building investment, a finding with direct implications for how international development organisations, bilateral donors, and multilateral agencies prioritise their educational technology investments in Global South HEIs.

**Advancing Complexity Theory in the AI-Environmental Education Palace**

This study findings support complexity-conscious pedagogical design principles for AI-enhanced environmental education. First, the principle of emergent learning design: AI-environmental education should be designed to occasion rather than transmit ecological understanding, creating conditions active engagement with complex datasets, collaborative interpretation, iterative scenario exploration within which emergent complexity consciousness can arise. Second is the productive uncertainty principle, which posits for  students' exposure to the model limitations of AI ecological predictions. Third is the scalar integration principle, which ensures that AI-environmental education should engage HE students with ecological dynamics across spatial and temporal scales thereby developing their AI skills, which complex ecological systems demand. Also, the adaptive assessment principle, which ensures that learning assessment in AI-enhanced environmental education should be adaptive in relation to systems thinking and sustainability agency through qualitative, and reflexive instruments rather than reducing complex learning to standardised performance metrics.

**The Normative Horizon: What Kind of Environmental Education Does the Planet Need?**

The discussion of the study findings ultimately converges on a normative question that transcends methodology and even theory: what, at its deepest level, is AI-enhanced environmental education for? The evidence base documents impressive gains in ecological literacy, systems thinking, and sustainability agency competencies for individual professional development and institutional sustainability performance. But the planetary scale and moral urgency of the ecological crises that predictive AI models are documenting demand that the normative ambition of environmental education extend beyond competency development to the cultivation of what might be termed ecological citizenship: a profound, affectively grounded, ethically committed, and politically engaged orientation toward the living systems upon which all human and non-human futures depend. Furthermore, this study findings suggests that predictive AI modelling, when deployed within theoretical, pedagogically skilled, and institutionally supported environmental education programmes, possesses genuine potential to contribute to this deeper ecological citizenship formation through the systemic insight of its complexity modelling, and the political clarity of its sustainability implications.

Whether this potential is realised depends not on AI but on the educational, institutional, and political choices that shape how AI tools are deployed, for whom, with what pedagogical intentions, and in service of what vision of human-ecological relationship.

The Decolonial Imperative: Toward Epistemically Just AI-Environmental Education

This particular finding narrates and advocates for decoloniality in algorithmic bias and the marginalization of the Global South. A truly transformed AI-enhanced environmental education should portray ecological and social justice which is developed exclusively on ecological data, pedagogical models and epistemological frameworks developed and or produced by the Global South. Furthermore, this must be built on a foundation that creatively integrates diverse ecological knowledge systems, including Indigenous technology, ecological wisdom developed in Africa and incorporates community-based AI models, curriculum designs environmental monitoring and pedagogical frameworks developed in the African space for AI-enhanced environmental education. This decolonial imperative is a scientific and pedagogical necessity. Indigenous technology systems encode ecological observations spanning centuries and millennia which temporal depths that instrumental scientific monitoring cannot match, thus providing irreplaceable insights into long-term ecosystem dynamics, species interactions, and ecological threshold behaviours that AI models trained exclusively on recent satellite data fundamentally lack. Integrating this knowledge into AI environmental education is therefore a scientific enrichment of the knowledge base upon which AI ecological models, and the environmental education they enable, must be built. This discussion thus arrives at its normative destination of an AI-enhanced higher environmental education that is technologically sophisticated, computationally resourceful, pedagogically relational, globally informed and locally grounded, scientifically rigorous and ethically committed, which honours the complexity of ecological systems and the full diversity of human knowledge for the purpose of sustaining the living world upon which all futures depend.

This study makes an original and theoretically grounded contribution towards advancing the frontier of AI-enhanced environmental education scholarship. The study is offered in the spirit of genuine collaborative intellectual inquiry, an invitation to educators, researchers, policymakers, and institutional leaders to engage critically, build empirically, and act transformatively in service of the ecological futures that HE has a unique responsibility to help secure. In essence, this study concludes with a reflection that is simultaneously scholarly and deeply human. The ecological crises that predictive AI models are documenting with unprecedented precision and urgency such as the accelerating loss of biodiversity, the advancing depletion of freshwater systems, the destabilisation of carbon cycles, the fragmentation of forest ecosystems are lived realities threatening the wellbeing of billions of people and countless non-human species across the planet. HE’s response to these realities centres on what HEIs are for, whose futures they serve, and what kind of world their graduates are being prepared to inhabit, understand, and actively shape. The study findings suggests that predictive AI modelling, when deployed with pedagogical wisdom, institutional commitment and epistemic justice possesses transformative potential to deepen environmental education's contribution to that shaping by producing HEI graduates who do not merely know about ecological systems but feel responsible for them, who do not merely understand sustainability frameworks but act from them, and who do not merely analyse environmental data but are moved by it toward the collaborative, creative, and courageous action that genuine ecological citizenship demands. Realising this potential requires that HEIs resist the twin temptations of techno-optimism, i.e. the naive faith that AI tools will themselves solve the pedagogical challenges of environmental education and institutional inertia through the comfortable reproduction of existing curricula in the face of mounting ecological urgency. It requires instead the kind of deliberate, theoretically informed, justice-oriented, and transformatively ambitious educational leadership that this study identifies as the HEIs commitment to advancing ecological systems sustainability through the most powerful instrument at their disposal: the educated human mind, transformed in its understanding of and relationship with the living world. Hence, the planet does not need more graduates who know that ecosystems are complex. It needs graduates who have genuinely reckoned with that complexity and have sat with the disorienting dilemma of AI-generated ecological forecasts and emerged with transformed ecological consciousness as well as renewed sustainability agency. That transformation is what education, at its deepest level, is for and is what this study in its totality seeks to advance.

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